Identifying and Quantifying the Resilience Dividend using Computable General Equilibrium Models: A Methodological Overview

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Abstract

This paper introduces the concept of accounting for the net co-benefits (the resilience dividend) associated with community-level resilience planning. Two solutions to the same resilience issue may often have different associated co-benefits that accrue on a day-to-day basis even if a disruptive event has not yet occurred. Thus, assessing potential community resilience projects requires taking (positive or negative) co-benefits (i.e., the resilience dividend) into account. Without including positive (negative) co-benefits, the total value of a resilience project may be underestimated (overestimated). But to date, quantification of the net co-benefits of resilience planning is not often addressed in the literature, as it is not a straight-forward task. We overview a methodology developed using spatial computable general equilibrium (SCGE) models to quantify and assess the distributional effects of the resilience dividend arising from a proposed resilience plan. In turn, such assessments can be used in benefit-cost analyses (BCAs) and other economic project assessments when comparing among potential resilience projects. Economically, good decision-making requires prioritizing feasible projects with the greatest overall net-benefit to the community. We provide a way for co-benefits to be quantified and subsequently accounted for in formal assessment by communities choosing among resilience plans.

Keywords
community resilience, adaptation, mitigation, community planning, macroeconomics

1. Introduction

The number of observed large-scale disruptive natural events is rising – by about five percent a year since 1960 (Schultz and Elliott 2013). Kunreuther and Michel-Kerjan (2009) note that costs of natural disaster-related losses jumped from $93.3 billion in the 1960s to $ 778.3 billion in the 1990s. Strömberg (2007) notes that population growth (meaning more people encounter disasters) explains only about half of this increase. After all, there has also been a marked reduction in lives lost due to natural disasters.40 An important

[40] From 1900 to 2003, 62 million deaths resulted from natural disasters throughout the world. But 85 percent of those deaths occurred between 1900 and 1950 (Bandyk 2010).

factor in the increased number of reported disasters is likely better reporting and more responsive aid organizations as well as changing climatic trends.

As weather-related covariate risks and the associated costs of losses increase in the future, households and businesses need resilient strategies and coping mechanisms that reduce the effects of such disasters, in terms of intensity and economic losses. Generally, as assets vulnerable to natural disasters increase in value, so do costs of protecting these assets and infrastructure through insurance and/or other means of planning. Thus, the concept of choosing resilience plans that encompass co-benefits to the community on a day-to-day basis in the absence of a disaster event has garnered increased interest recently (e.g., Rodin 2014). Accounting for the net co-benefits (i.e., the "resilience dividend") of a resilience project can often produce a convincing business case for undertaking the project. This is especially pertinent when the return on investment may be much lower if a disaster does not take place during the time frame of the analysis. Fung and Helgeson (2017) define the "resilience dividend as the net benefit (or cost) that accrues, from investments aimed at increasing resilience, in the absence of a disruptive incident over the planning horizon," and provide a comprehensive overview of the resilience dividend as a useful metric for community resilience planning and reviews measurement and assessment efforts.

This paper provides an overview of the importance of accounting for the net co-benefits of resilience planning and explores a novel approach to quantifying the resilience dividend. The methodological approach introduced uses a spatial computable general equilibrium (SCGE) model of the community being assessed for resilience planning to identify co-benefits (co-costs).

The remainder of this paper is organized as follows. Section 2 provides context by reviewing the literature and some approaches that strive to quantify the resilience dividend, which to date has been largely dealt with through qualitative case studies (Rodin 2014). The section highlights the importance of considering the economic flows from the resilience dividend in a dynamic, quantifiable manner. Section 3 provides an overview of CGE and SCGE modelling. Section 4 provides a detailed discussion of data required to use SCGE models with special focus on the characteristics of a CGE model designed to trace co-benefit-related flows and distributional effects. It discusses the complex nature of obtaining data for CGE models and the accompanying social accounting matrix (SAM). This section offers insight as to the ideal data versus data that is sufficient in most cases. Section 5 takes the data discussion towards methodological implementation. Finally, Section 6 highlights next steps and future work to develop a full case study based on the SCGE net co-benefits methodology introduced in this paper.

2. Background and Motivation

2.1. The importance of considering resilience-related co-benefits

Economic valuation techniques, such as benefit-cost analyses (BCAs) for community resilience planning alternatives, are often not a straightforward process. In nearly all cases, measuring the economic impact associated with resilience planning requires a better understanding of the costs and indirect losses41 to maintain a full accounting of the major cost elements. On the loss side, an understanding of the cascading indirect losses is critical to true valuation of losses stemming from a natural disaster. Furthermore, quantifying and accounting for uncertainty in estimates related to these costs and losses is complicated due to the nature of disaster events and the uncertainty surrounding their occurrence and effects. Finally, measuring net co-benefits (i.e., the resilience dividend) is needed to articulate the business case for resilience planning. Often plans that could alleviate vulnerability to a large-scale disruptive event, but are not called into action due to the absence of the event (in a given time frame), are perceived as a poor investment. Consideration of co-benefits (co-costs) is generally good practice,42 as the impacts of these values can be pivotal in identification of the most effective and efficient resilience plan.

When quantification of co-benefits is possible, they should be folded into the net-present valuation (NPV) of resilience plans (see Gilbert et al. (2016) and Helgeson et al. (2017)). Yet, much like cascading indirect losses, there are likely cascading and wide-spread effects of identified co-benefits. Thus, the use of computable general equilibrium (CGE) models that employ actual economic data from a community to estimate how an economy might react to changes in policy, technology, or other resilience planning initiatives allow for a better understanding of distributive effects of net co-benefits. Specifically, spatial computable general equilibrium (SCGE) models can be employed to indicate the distinction of flows throughout different areas of a community, which may be more or less vulnerable to and affected by a disruptive event. CGE and SCGE models are overviewed in Section 3.

2.2. Defining and quantifying the resilience dividend – overview

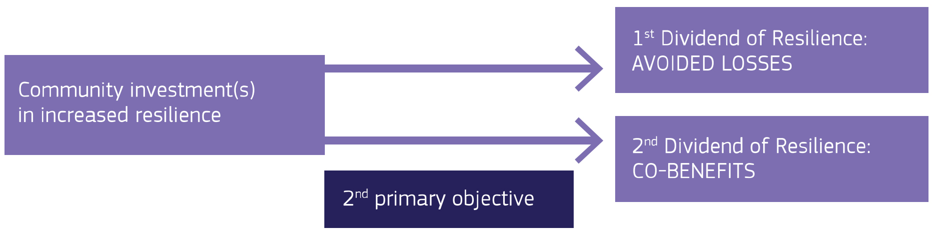
To date, the literature is largely dominated by definitional discussions and qualitative assessments of co-benefits (co-costs) and the resilience dividend using case study examples (e.g., Rodin 2014). In a review of the literature, Fung and Helgeson (2017) found that co-benefits fall into three broad categories: 1. Objective-based, 2. Intent-based, and 3. Externality-based.43 The objective-based definition of co-benefits fits well into the methodology overviewed in this paper. Objective-based definitions regard co-benefits as benefits to secondary objectives of a policy (ibid.). For instance, changed zoning in a community may have a primary objective of shifting commerce away from the flood zone, while secondary objectives may include stimulating economic growth in an area of town that becomes favorable for re-locating businesses.

As noted in Fung and Helgeson (2017), research on the co-benefits of climate change mitigation and adaptation is substantial, while co-benefits in the context of resilience planning is still relatively nascent.

[41] To date, direct losses tend to be better documented.
[42] See Gilbert et al. (2016) and Helgeson et al. (2017)
[43] Externalities are defined by benefits (costs) that accrue to third parties. As such we treat them fundamentally different from values that are encompassed by the resilience dividend. For a discussion of externalities versus non-disaster related benefits (i.e., the resilience dividend), see Gilbert et al. (2016) and Helgeson et al. (2017).

Much of the literature on co-benefits of resilience planning is centered upon the developing country context. Furthermore, there appears to be relatively few scholarly works that deal with quantification, opposed to qualitative assessment, of co-benefits. This is understandable, as much of the work that explicitly encourages quantification of co-benefits when possible is based upon ex ante analysis, such as BCA, to determine effective investment decisions across a suite of options. In an ex ante BCA it is naturally complicated to capture full valuation of co-benefits, which often are apparent only after a plan is put in place. In other words, some co-benefits of significant value may not be readily obvious during the planning phase without a larger scale model that can incorporate spatial and/or distributive effects. But quantifying the full co-benefits ex post is not a simple task – modeling the economy is complex, it is likely very unclear how the co-benefits flow through the economy, and since the decision was already made, stakeholders may be less inclined to spend money and other resources on studying the issue.

Figure 1. Conception of the resilience dividend as net co-benefits used in this paper and upon which the proposed methodology is based.



A series of World Bank reports have presented the resilience dividend as arising from a "Triple Dividend of Resilience" as largely relevant to disaster risk management (DRM) (e.g., Tanner et al. 2015, Tanner et al. 2016, Mechler et al. 2016). This triple bottom line consists of: 1. avoided or reduced losses, in the event of a disruptive event occurring; 2. increased economic resilience from reduced disaster risk; and 3. co-benefits for development. Elements one and two make up the first dividend of resilience, while the third element makes up the second as shown in Figure 1. Though these three "dividend" sources do not map perfectly onto the developed country context, the prevailing message is that budgeting for contingent liabilities such as disaster risk, especially ex ante a disruptive event, is nearly impossible without accounting for the resilience dividend.

A recent RAND report (Bond et al. 2017) describes a Resilience Dividend Valuation Model (RDVM) and its application to six case studies in the developing country context. It should be kept in mind that Bond et al. (2017) define the resilience dividend as "the difference in net benefits from a project developed with a resilience lens versus one that is not." This definition is much broader than the definition we use (Fung and Helgeson 2017), which is concerned with net benefits above and beyond benefits expected to accrue directly to the goal of resilience to a disruptive event.

The RDVM largely looks at the resilience dividend as the positive net benefits generated between a resilience project and a business as usual (BAU) counterfactual. The elements of the RDVM are largely based on typical meso- and macro-economic elements within a production-oriented framework: 1. Capital stocks/assets, 2. Production functions and allocation mechanisms (i.e., institutions), 3. Social welfare function, 4. Shocks and stressors (both ex ante and ex post), and 5. Project interventions (based on resilience).

Of the six case studies considered in the RAND Report, three are ex ante and three are ex post assessments. Three of these six case studies resulted in no quantifiable resilience dividend assessment (two ex post and one ex ante) and three result in a partial quantitative assessment of the resilience dividend (two ex ante and one ex post). In many cases the lack of a full quantitative resilience dividend analysis is discussed in the context of too little data being available through pre-existing documentation and data.44 Another challenge discussed is that only one state of the world is observed—the counterfactual is unobservable—it is then difficult to rely on observations made with or without a resilience intervention (i.e., plan) in place (ex ante or ex post).

The systems model approach we propose for assessing the resilience dividend is typically based at the meso-level of a community's economy and allows us to make assessments of the resilience dividend and the associated indirect flows throughout the economy. Many of the elements discussed in the RDVM in terms of a production-oriented framework are reflected in the SCGE model approach we describe in this paper. In our approach, we can theoretically obtain community-level data for any US-based community that may be engaged in resilience planning and assess ex ante potential resilience dividends as well as ex post performance. There are limitations inherent in this approach; this is especially the case for micro-level economic activity, at the household, opposed to community levels. This approach is a first step toward creating dynamic quantitative valuation of the resilience dividend and distributive effects.

3. Computable General Equilibrium Models – Introduction and Overview

3.1. CGE General Details and History

The characteristics of CGE models make them a reasonable choice for exploring the effect of large disruptive events on a community's economic activity as well as effects of resilience planning. This section provides a general outline of CGE and SCGE models. Specific use of an SCGE model and the relative data requirements is discussed in Section 4 of this paper.

There are two major reasons for exploring the use of CGE models to quantify the resilience dividend. The first being that while qualitative results are useful, understanding the relative effects in magnitude of a shock and the associated resilience plan as well as the resilience dividend is important. The second being that solid micro-foundations enhance our understanding of resilience planning and how a resilience dividend affects consumers, producers, and government in an economy. Overall, the aim of the CGE model approach is to convert the abstract representation of the community's economy into a realistic, solvable approximation to assess direct and indirect benefits of resilience planning. In turn, these assessments can help inform values used for co-benefits (co-costs) of resilience planning in (ex ante) BCA during planning phases.

Input-output (I-O) analysis (Leontief 1941) has been used for assessing the impact of a change in the demand conditions for a given sector of the economy.[45] I-O models/coefficients assume constant returns-to-scale for associated production functions and prices are also assumed to remain constant. Extension of the I-O model to a social accounting matrix (SAM) framework is performed by partitioning the accounts into endogenous and exogenous accounts. Sadoulet and de Janvry (1995) note that endogenous accounts are those for which changes in the level of expenditure directly follow any change in income, while exogenous accounts are those for which we assume that the expenditures are set independently of income.

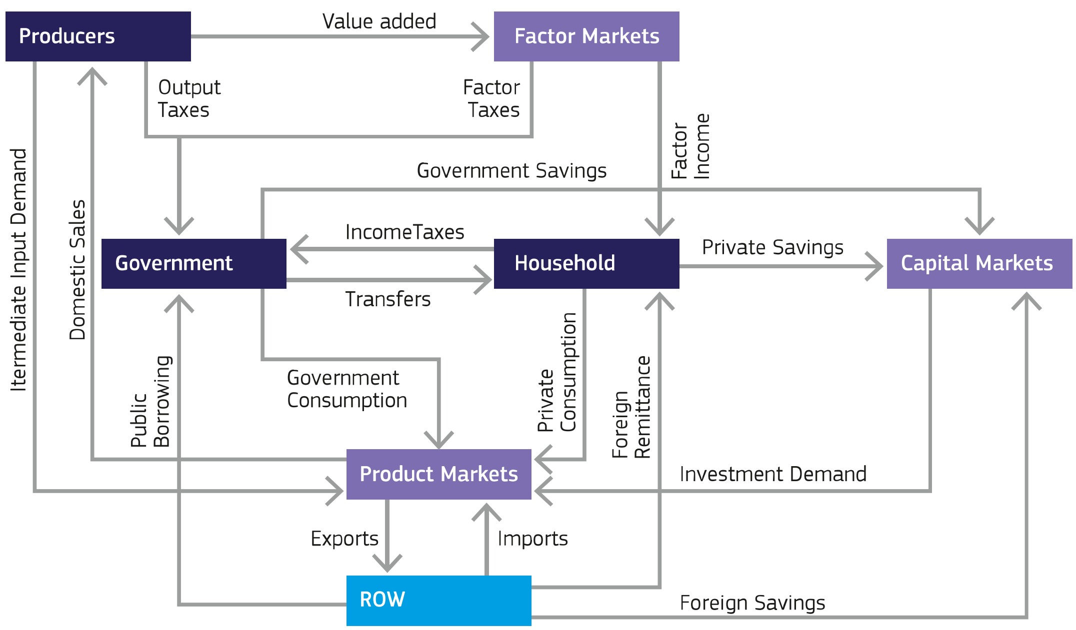
The CGE model encompasses both the I-O and SAM frameworks; this occurs because demand and supply of commodities and factors are assumed to be dependent on prices. Figure 2 provides a schematic overview of the typical elements of a CGE model. A CGE model simulates the working of a market economy in which prices and quantities adjust to clear all markets. For example, households maximize their welfare, the government is assumed to have a balanced budget, and resources are limited and costly. Effectively, a CGE model

[44] This data was not necessarily collected initially for use with the RDVM in most cases (Bond et al. 2017).

[45] See Section 4.7 for further discussion.

specifies expected behavior of optimizing consumers and producers, as well as including community government (e.g., taxes) as an agent to capture transactions in circular flow of income (Robinson et al. 1990).[46]

Figure 2. Schematic of main components in a CGE model. Note that ROW refers to the “Rest of the World”, that is the aggregation of all economic transactions between the selected region under consideration and those not within the selected region.



3.2. Comparative-Static or Dynamic CGE Models?

Many CGE models are comparative-static; they are used to model the reactions of the economy at only one point in time. In such cases, the model is interpreted as demonstrating the reaction of the economy in a future period to one (or more) external shocks, policy changes, and/or resilience planning efforts—in our application, the resilience dividend. That is, the results show the difference (usually reported in percent change form) between two alternative future states (with and without the resilience plan in place). The process of adjustment to the new equilibrium is not explicitly represented in such a model, as the temporal element of a CGE model is not well defined. But it is possible to distinguish between short-run and long-run equilibria (e.g., looking at whether capital stocks are allowed to adjust in a given run of the model).

By contrast, dynamic CGE models (e.g., Pereira and Shove 1988) explicitly trace each variable through time—often at annual intervals. These models are more (temporally) realistic than comparative-static models; however, the data requirements are greater and they are generally more challenging to construct and solve. Furthermore, in the case of resilience planning which already encompasses a great deal of uncertainty, they require that future estimations are made for all exogenous variables—not just those affected by the shock,

[46] The CGE model takes a Walrasian neoclassical general equilibrium approach—the main equations that need to maintain equilibrium are derived from constrained optimization of the neoclassical production and consumption functions. Producers operate at a level as to maximize profits (minimize costs). Production factors – labor, capital, and land – are paid in accordance with their respective marginal productivities. Consumers are assumed to be subject to budget constraints, but otherwise maximize their utility. At equilibrium, the model solution at equilibrium provides a set of prices to clear commodity and factor markets within the modelled community’s economy (see Bandara 1991).

policy change, and/or resilience plan. Furthermore, consistency problems may arise because variables that change from one equilibrium period to the next may not be consistent with each other in the fixed period of change.

Thus, we propose using a comparative-static model set-up. In some cases, the data required for the CGE assessment of the resilience dividend (see Section 4) will be available in different years. Thus, creating a CGE model for a period before the resilience plan integration and another CGE model following the integration may be a realistic way to provide a dynamic understanding of the resilience dividend.[47]

3.3. Spatial CGE Models

SCGE models deal with distributive effects in a manner that makes a great deal of sense when dealing with resilience planning against large-scale shocks (e.g., natural disasters). To date, SCGE models have been used to assess economic impacts of infrastructure investments and policies, especially in the area of transportation (e.g., Ivanova et al. 2007 and Miyagi et al. 2006). Multi-regional input-output models are the closest relatives to SCGE models, but they are not able to fully capture price and quantity effects as they do not allow for substitution effects.

Thus, SCGE models are a natural fit for exploring the resilience dividend and the geographic distribution of the relative effects. In our discussion of data requirements and setting up the resilience dividend assessment we assume use of SCGE modelling.[48] Section 4 describes the specific data required to create a SCGE model to quantify the resilience dividend and determine distributive effects.

4. Data Required

4.1. Social Accounting Matrix (SAM)

The primary goal of data collection is to develop the social accounting matrix (SAM). A SAM can generally be described as “an organized matrix representation of all transactions and transfers between different production activities, factors of production, and institutions … within the economy and with respect to the rest of the world” (Hirway et al. 2008). In short, it quantifies all cash flows between pertinent actors within an economy. The SAM serves as the core of the CGE analysis, as it defines the base relationships between sectors, households, labor markets, and other key actors in the economy that the CGE model uses to determine the impacts of policies and shocks. The World Bank (Round 2003) notes that there are three key features to a SAM: 1) they are square matrices, 2) they are comprehensive, including all economic activities of the system, and 3) they are flexible in how they may be disaggregated and what parts of the economic system are emphasized. The following sections provide available sources for acquiring the data needed to build a SAM based on the method for constructing a spatial SAM and CGE model developed in Cutler et al. (2017). The subsequent data sources are not the only ones available, but are more commonly used than others or are most capable of filling data needs. There is a comprehensive discussion of methods for SAMs and CGE models in Cutler et al. (2017). Example applications and case studies using CGE modeling can be found in Cutler et al. (2017) and Schwarm and Cutler (2003).

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[47] This solution implies a retroactive study opposed to a perspective study in which the outcomes of the economy after the resilience plan is enacted is completely unknown.

[48] For more on SCGE, see Bröcker and Korzhenevych (2011).

4.2. Quarterly Census of Employment and Wages (QCEW) data

4.2.1. Summary

The quarterly census of employment and wages (QCEW) is a Bureau of Labor and Statistics (BLS) program that reports the quarterly count of employment and wages for employers, broken down at the industry (defined by the North American Industry and Classification System (NAICS) code) level and geographically at the county, Metropolitan Statistical Area (MSA), state, and national levels. The QCEW covers roughly 95 % of all U.S. jobs (BLS Website). This data is an excellent source to determine wage payments, employment, and number of firms by industry.

4.2.2. Challenges

Because the data contains commercially identifiable information (CII) and, potentially, personally identifiable information (PII), firm-level QCEW data is not publicly available and must be requested through an appropriate state or federal government agency. This process can be time consuming and may require payment to cover the cost of labor. There are also restrictions on how it can be used and reported, namely steps must be taken to mask any CII or PII. This is typically done through ensuring a minimum number of firms in each industry and making sure that no single industry has a large percentage of its data coming from one firm, regardless of how many firms are in the industry.

While one of the best sources of data for building a SAM, there are other ways to obtain the same information, though the data will typically be pre-aggregated to address CII and PII concerns and thus, less refined. The advantage of obtaining firm-level data is that a researcher can customize how the data is aggregated. In particular, the data can be aggregated with respect to sectors defined by the researcher, potentially breaking these out spatially using the establishment address. See Section 5.1 for more details.

4.3. LEHD Origin-Destination Employment Statistics (LODES) data

The Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data collected by the Center for Economic Studies at the US Census Bureau details employers, their employees, and the flow of jobs over time and space. This data allows for the mapping of labor flows between regions within and beyond the scope of a given CGE model. This data can be especially useful in modeling the commuting patterns of employees in and out of town as well as movement between a city's districts. The value of this data is in its ability to specify the transportation needs of the community under analysis and evaluate how that community would be impacted by various disaster scenarios or other shocks. For instance, the severity (measured in economic damages) of a hazard event that results in a bridge closure is likely to be informed by the extent to which the local community relies on that piece of infrastructure to commute to work or flee the ill-effects of the hazard in question.

4.4. Public Use Microdata Sample (PUMS) data

4.4.1. Summary

Public use microdata sample (PUMS) data is collected by the U.S. Census Bureau and reported at various intervals. The dataset relies on the use of American Community Survey (ACS) data. Unlike the decennial census, ACS surveys are yearly and not nationwide. Roughly one in thirty-eight households are invited to take the survey every year (U.S. Census Bureau 2017). The data collected in the ACS is very similar to the data collected during the decennial census. The household income distribution can be obtained from this dataset at varying geographic levels ranging from as large as the United States, down to ZIP code tabulated areas. The primary data set of interest from the PUMS data is the employment by sector and the aggregated wage payments by sector. These allow the SAM to differentiate between different labor groups.

4.4.2. Challenges

Access to individual level data is not available without the permission of the U.S. Census Bureau due to the large amount of PII and its access and use is subject to severe restrictions. At present, getting access to Census data requires showing that the use of the data would benefit the U.S. Census Bureau in some way. This is not necessarily easy to prove and, even if access is given, may take a significant amount of time to obtain. If obtained, restrictions on use, where and how the data can be accessed, and how data can be reported add further barriers to use. The publicly available data through the ACS website comes with no restrictions, but is pre-aggregated in a way that may not match one-to-one with the way industries are defined in other datasets. This issue may or may not be important depending on how industries are aggregated in the SAM, but nevertheless it is the most readily available data. The use of microsample data means the given value is extrapolated from the subset of U.S. homes that took part in the survey. If the desired year happens to coincide with a decennial census, then the use of decennial census data is possible.

4.5. County and City Assessor data

4.5.1. Summary

The development of a CGE model involves the construction of an accurate snapshot of a specific economy at a given point in time so that the resulting model may be calibrated to represent the community under investigation. One key component of the CGE model is the accurate representation of the value of land and capital within the regional economy. Estimates of household expenditures on various classes of housing services for disaggregated groups of households is also a key attribute of the regional economy that must be modeled with the greatest level of fidelity possible. City and County Assessors offices collect, maintain, and make available to the public this information on the building stock within their respective political boundaries.

4.5.2. Challenges

The challenges inherent in working with public data are generally present when working with property tax assessment data. While very accessible, property tax assessment data is freely available for many communities, usually through the county assessor's office, it can and often does entail typographical errors that complicate the matching of the built environment to the businesses and residences therein. Missing data can be a problem for some variables reported in the property tax assessment data. There is considerable variance in the degree of detail and historical support of reported data across communities. Data may be reported in a manner that is not consistent across all years of interest to a given project. The classification and categorization of the built environment may change over time as data systems are improved and expanded.

4.6. City Budgets and the Comprehensive Annual Financial Report (CAFR)

4.6.1. Summary

Comprehensive Annual Financial Reports (CAFR) are documents containing details of the financial state of a given governmental entity such as a state or municipality. These documents are useful resources for the determination of local government tax revenue, expenditures, and employment. The CAFR provides the information necessary to decompose employment and expenditures into constituent government "industries"; education, public health, public safety, park and recreation, and others. This information is critical to efforts to properly size and disaggregate the government sector within the CGE model. CAFRs tend to be different across communities; one constant tends to be that the CAFR provides an excellent source of tax revenue and expenditures. The CAFR can also be a reliable source of data on the expenditure of federal funds in the local economy. Within some CAFRs, there is a Schedule of Expenditure of Federal Awards which lists information for each federal grant awarded to the city (or other government entity) organized by the granting agency and program title.[49] This is a useful source of information for corroborating the timing of federal assistance programs that target disaster response among other pressing community needs. While the data in the CAFR on federal assistance may not be sufficiently disaggregated to model at the establishment or industry level, it is useful for ensuring the magnitude of relevant programs.

4.6.2. Challenges

The CAFRs are data-rich documents, but they generally contain information that must be reformatted or reorganized if it is to be of further use to the CGE modeler. While there are standards of presentation and content associated with the CAFRs, the exact format of the reports can differ over time, complicating long-term trend analysis.[50] It is possible that the CAFR for any single year may include federal grants that are only present in that year. Care should be taken to avoid treating grant awards as recurring components of local government finance within the CGE model.

4.7. Bureau of Economic Analysis (BEA) data

4.7.1. Summary

Bureau of Economic Analysis (BEA) data is vital in building the SAM. The BEA data set provides the necessary tables to determine I-O coefficients and the values required to develop the relationship between investment and the stock of capital. The I-O data is generally taken at the national level and, in its raw form, gives the raw dollar amounts of input from each industry and the total output from each industry. These values can be used to determine I-O coefficients, which represent how much input each industry requires from every other industry in order to produce a dollar's worth of output. I-O coefficients define the flow of money between industries, and thus the linkages between industries necessary for the CGE model to determine how impacts on one industry flow to another.

The data for the investment capital linkage (CAPCOM) matrix comes from the BEA "Capital Flow" data. This data tracks the investment in new structures, equipment, and software by using industries. In essence, it measures how many commodities a specific industry purchases for investment from another industry. Like the I-O data, the CAPCOM tracks the interdependencies between industries; however, it focuses on new investments instead of required input. The raw data is taken from the I-O commodity categories (as opposed to the National Income and Product Account categories), which are in terms of producers' prices.

Other useful data from the BEA includes the BEA employment estimates and the BEA income estimate, which are available at varying geographical levels. While other datasets offer data on these values that are better suited for use in the SAM, the BEA estimates provide a useful check for their totals.

4.7.2. Challenges

As the BEA data is derived from multiple sources using CII, including the U.S. Census Bureau, all publicly available data is pre-aggregated, meaning industry classifications may not match one-to-one between other data sets. The more detailed underlying data is subject to the similar requirements for access, and restrictions on use, as mentioned for the ACS data.

[49] A CAFR may not include a Schedule of Expenditure of Federal Awards if the total amount of federal awards expenditures by a non-federal entity is less than $750 000 dollars in the reporting year. Title 2 U. S. Code of Federal Regulations Part 200, Uniform administrative requirements, cost principles, and audit requirements for Federal awards provides the guidance on whether or not a CAFR must contain an audit of the expenditure of federal grant awards.

[50] Accounting and financial reporting standards for state and local governments are codified by the Government Accounting Standards Board (GASB).

4.8. Informal data from community leadership and agencies

4.8.1. Summary

Depending on the exact research question and scope of the resilience dividend, the community being studied itself may prove to be an invaluable source of information. In the context of resilience, local officials can offer a unique and comprehensive perspective on the impact of a natural disaster on the community. Conversations with the City Manager's Office, Emergency Management, and (public or private) Economic Development teams can reveal priorities with respect to both the immediate response to a disruptive event type faced by the community, as well as short- and long-term recovery efforts and community goals. For instance, while a researcher may be aware that a community is investing in flood resilience, it is not obvious to an outsider where and how a community is investing its resources. Moreover, community officials can help a researcher compile a more complete picture of funding sources, both private and public.

Conversations with community officials can also provide perspective on local economic trends and goals, both irrespective of the potential disaster and specific to the disaster occurrence. While official data may suggest that manufacturing is an important sector to a community, the community itself may emphasize information technology as a growing sector being targeted with economic incentives such as tax breaks. Moreover, the community can provide insight into regional trends. For instance, business improvement districts may be integral to long-term community resilience. Certain neighborhoods may be of particular interest to a community (e.g., revitalization of downtown commerce). Such trends may inform the modeling step, in terms of how a researcher defines the productive sectors—especially spatially—and consequently the aggregation of official data for constructing the SAM.

4.8.2. Challenges

While the information gathered from conversations with community officials comes from authoritative sources, the "data" collected is informal. Incorporating the array of information into constructing a CGE model is less about collecting input data and more about guiding research direction. The biggest challenge arises from knowing what to ask. As an outsider, a researcher may have preconceived notions of what issues matters most, and community officials may be more than happy to answer questions about such issues. It is important to remember that what matters most to a community may differ from what a researcher thinks matters most. Gaining an understanding for a community's priorities can provide the proper context for analyzing a community with a CGE model. Moreover, it is important to keep in mind that not all communities may be organized enough to provide the necessary data, and some may be reluctant to the idea of providing the information. Even when community officials are willing to share information, they may be constrained by regulations, budget, or time.

4.9. Third Party data

4.9.1. Summary

If other data sources are not viable for use in the SAM, third party data may also be used. Third party datasets typically will provide the requested data aggregated as requested for a fee. Impact Analysis for Planning (IMPLAN) data (IMPLAN Group LLC) is a commonly used third party dataset derived for economic analysis. Their data includes premade SAMs at the national, state, and county level that can be augmented by the user with different data or relationships (RESI 2006). Other datasets are available, for example Thomson Reuters (Thomson Reuters 2015) and FactSet (FactSet 2017).

4.9.2. Challenges

Due to the proprietary nature of third party datasets, it is impossible to know all of the details of how the data were developed. While companies do describe processes and underlying sources, they invariably do not include everything in order to preserve any business advantages they might possess. The data also must be purchased and the fees may be prohibitive depending on the nature of the analysis and the party or parties required to purchase it. Care also must be taken to ensure that the data available from the third party is the actual data required.

4.10. Geographic Data

4.10.1. Summary

Economies have long been modeled as systems disembodied from their physical components. The increased adoption of geographic information systems (GIS) by firms and government entities allows for the spatial disaggregation of economic data with location records. Geographic data enables the introduction of explicit spatial considerations into the CGE model, which brings it towards an SCGE model. It is reasonable to assume that similar shocks may propagate through an economy in patterns that are informed by the topology of the built environment and regional geography. In many cases, data used for the CGE model includes spatial identifiers such as street address. GIS tools such as geocoders that produce longitude and latitude coordinates when fed address information, allow for the geolocation of individual business establishments and residences. In addition to matching firms and parcels, geocoding is instrumental to the process of defining the districts into which the local economy is divided. Once the geographic coordinates of each parcel are obtained, the parcels can be plotted and sorted into their districts using ArcGIS software. The importance of spatial linkages to overall impacts from a hazard may differ with the economy and hazard in question. There is a fundamental tradeoff between increased spatial disaggregation using GIS data and reduced complexity within the SAM. Establishing a distinct district for each establishment or residence would intractably complicate the SAM. Neglecting to incorporate any spatial information into the SAM may aggregate contravening trends, delivering results that mask important underlying trends in economic growth and hazard recovery.

4.10.2. Challenges

The fundamental challenge of working with GIS data is rooted in its variable quality and availability. GIS data may be missing for some public records and can be difficult to extract from data with messy variable coding. Improperly assigning establishments to the wrong district, as a result of bad address data, could impact the validity of a spatial CGE model. Different geocoding tools can produce geographic coordinates for the same record that disagree by small or large distances. The judgement calls that must be made to render this GIS data usable may ultimately be unjustifiable. Furthermore, GIS data can be inherently identifying when merged with other sources of data. Care must be taken when working with GIS data to avoid the unintended disclosure of CII and PII.

5. Methodology

5.1. Combining the Data

Combining the data from Section 4 into the SAM offers several benefits. First, in many cases it is often necessary. No single data set from Section 4 contains all of the required data for the SAM, with the possible exception of that provided by a third party vendor. Second, all of the data can be verified by the model builder. Moreover, each dataset can be verified independently by the model builder and better tailored to particular assumptions. Using third party data limits how much verification and customization is available for the analysis. Most third-party datasets are heavily vetted; however, it can be beneficial to be able to check the underlying data. Third, working with the data directly can allow further insights outside the original scope of the model. Trends may appear in one dataset that wouldn't be visible in working with only the final SAM.

While there are benefits to using multiple sources of data, the use of the varied sources in Section 4 can create challenges when folding them into the final SAM. One example of this complication is attempting to derive the I-O and CAPCOM data at the PUMS sector level using the PUMS defined industry codes. The BEA and PUMS data sets are both based on NAICS codes; however, they aggregate those NAICS codes into larger industry categories that do not match one-to-one with each other. If the industries are broadly defined then this is not necessarily an issue. For instance, if manufacturing industry data is provided without disaggregation, then the industry codes from the PUMS data and BEA data, while different, still fall entirely within the larger aggregated manufacturing sector. If manufacturing industry data is disaggregated, then there is no guarantee that the each PUMS industry code will have a corresponding BEA code, or codes, that match in terms of NAICS codes covered. In such cases a fuzzy match is required which will possibly lead to a NAICS code from a sector not in a specific PUMS industry code being in the IO table for that PUMS industry code due to the inconsistency. The alternative version where a PUMS industry code loses a corresponding NAICS code is also possible.

Another challenge comes from datasets not necessarily covering the same geographical area. For instance, the smallest division of the county assessor may be at the city level, while the smallest division in the PUMS data may be at the MSA level. In such cases, it may be necessary to scale numbers up or down based on some distribution of relevant data, to get geographic areas to match up. An example of this would be scaling down MSA level data for industry specific employment by labor group down to the city level based on the known distribution of industry employment in the city.

Using different data sets means the totals for some values obtained for the same geographic area, such as total employment, should be the same (if all data were perfect), but end up being different between data sets. Such differences are to be expected between data sets, as differences in what is or is not included and methods may end up resulting in different estimates. Still, the CGE requires consistency between key values in order to balance the SAM and run analysis. Similar to the situation of differing geographic areas, scaling numbers up or down to match may be required. However, these differences between data sources under such circumstances should be relatively close. Otherwise, there may be an unaddressed issue with the data.

Spatializing the SAM adds further complications. One issue that arises is the need to match industry level data to the spatialized components. This process is meant to allot the capital land value from the county property tax assessment data and the QCEW employment and wages to the appropriate industry sector. Matching on addresses is known to be a non-trivial task, as abbreviations, misspellings, date entry errors, and other consistency problems make getting the desired match difficult. Address standardization and fuzzy matching can alleviate this, but typically does not fully address the issue. The other complication with using the QCEW data in this context is that there are requirements on making sure all data is aggregated to the point that CII becomes masked. This is typically achieved by ensuring every industry has a minimum number of firms included to make it impossible to trace back the information to a specific firm. This means that industry sectors may need to be aggregated into larger sectors if they contain too few firms.

Spatialization also complicates the entry of sector related data into the SAM. Ordinarily, industries are assumed to be in the area of study and that is all. Spatialization divides industries into sub-regions of the study area. This means labor, households, capital value, and the I-O and CAPCOM tables need to reflect this division. For the I-O table, it can be done fairly simply if one assumes that the firms in any sub-region are essentially the same as the firms in the larger area. Under this assumption, all I-O coefficients are identical to the non-spatialized I-O table for every industry. Otherwise, effort must be put into understanding how firms differ in terms of inputs and outputs in each sub-region. The spatialized CAPCOM can be obtained by determining a distribution of investments based on available data, for instance, the distribution of workers, firms, or wages for all sub-regions, and distributing them accordingly.

5.2. CGE Coverage of the Resilience Dividend

The ultimate goal of the proposed SCGE modeling method is to quantify the resilience dividend. Therefore, it is important to understand what the SCGE model can and cannot quantify. A CGE model provides distributional impacts of shocks, policy changes, and the current status of the region. Distributional impacts allow the analyst to understand not only the overarching net impacts, but to whom and where those impacts fall and are distributed. Large economic effects will be easily discerned and the impacts can be selected to see how different scenarios may have played out in the region. Any effects of resilience actions that have co-benefits can be modeled to identify how those co-benefits manifest themselves throughout the economy and where they go. Thus, the resilience dividend can be quantified as a grand total, as well as determining who gets these benefits and where they go spatially. SCGE models may not capture the entirety of the resilience dividend in many cases. Non-market benefits that never actually materialize as real cash flows are not necessarily captured. Minor impacts may also be lost as the overall economic conditions may overwhelm them.

5.3. Additional Considerations

There are additional considerations that are important when using a SCGE model to quantify the resilience dividend. There are limitations to the CGE approach and full assessment of the resilience dividend may be best achieved using CGE methods in tandem with other economic methods.

5.3.1. The use of two CGE models

One critique of CGE models is that they are unable to fully capture the dynamics of an economy's response to a shock. Whether a community responds in acute fashion or slowly over a longer time period can have a considerable influence on the impacts of a given shock. The speed and persistence of a shock may be more informative than its magnitude. An advantage of having cross-sectional and panel data for a community is that response trajectories generated without full time specification can be calibrated using trends observed in the temporal data. The speed of recovery is of interest to communities considering their various options. The use of multiple CGE models may facilitate the corroboration of findings across approaches. Furthermore, if static CGE models are built using different baseline years that coincide with periods before and after a hazard event of interest, it is possible to see how the economy's response to an unrelated shock has changed over time. Of course, care must be taken to avoid the Post hoc ergo propter hoc fallacy if one is to employ two CGE models timed to before and after a hazard event. It is quite possible that other important structural changes are occurring simultaneously with the hazard.

5.3.2. Net Present Value, The EDGeS Tool, and CGE

As the CGE methodology uses I-O data there is some debate as to how time plays in CGE models. I-O tables generally represent a snapshot in time. However, CGE models use them to obtain the equilibrium following shocks to a system. How long it takes to reach that equilibrium after a shock is not a simple question to answer. In that regard, the time varying nature of the transition period from base state to post-shock state is currently difficult to model.

On the other hand, if one views the post-resilience action equilibrium as the base state for one case and the pre-resilience equilibrium as the base state for another case, it is possible to use the Economic Decision Guide (EDG) (Gilbert et al. 2016) methodology to examine these options based on Net Present Value (NPV). If a shock representing a disaster of an assumed magnitude is applied to both cases, the on-event indirect losses required using the EDG methodology can be obtained. Direct losses, such as structural losses, and response and recovery losses, such as temporary shelters, would need to be added in separately. The non-event related benefits can be estimated by examining the two cases' base states, with non-market benefits and externalities added separately from the CGE analysis, assuming these are not impacted by disaster related shock. The costs for each case should be known, thus all inputs required for the Economic Decision Guide Software (EDGeS) Tool (Helgeson et al. 2017) should be available.

6. Next Steps

The next step in this process is to complete an SCGE model based upon a community that has made changes based on resilience planning against a natural hazard event. A flooding event was chosen for the initial case study. Flood situations cannot be entirely prevented, but steps can generally be taken to prevent and minimize loss of property, interruption of business, and loss of life. Furthermore, floods are a leading cause of death from natural disasters in the United States. Flood-related fatalities are reported around 200 per year with about half caused directly by individuals attempting to drive through flood waters (Ashley and Ashley 2008).

Given the uncertain nature of most hazard events, in terms of timing, magnitude and path, we find flooding to be one disturbance event that may be more predictable than are other events, at least in terms of areas potentially affected (i.e., within a flood plain). Flood situations are variable and are often a by-product of other natural hazards, such as hurricanes. But there are instances when floods are standalone disturbance events (e.g., snowmelt, severe thunderstorms, prolonged rains) versus a bi-product or co-consequence of other disturbance events. In such cases of flood as a singular event, a geographic area in a given community may be affected more than other areas given soil, height above sea level, and flood protections. This is the case in general for Cedar Rapids, Iowa and the community's flooding events (p.c. S. Fowler, 13 March 2017).

We are in the process of finalizing the construction of the SAM for Cedar Rapids, Iowa with consideration for Linn County, Iowa. To date, we have collected detailed data for each category noted in Section 4 of this paper. This community made a number of deliberate choices in terms of zoning, retrofit construction, and new construction in the period since the major flood event of September 2008. Tate et al. (2016) assess the government buy-out process undertaken in Cedar Rapids. There are a number of additional projects that have now had time to mature since 2008, such as the revitalization of the downtown district and development of the McGrath Amphitheater (p.c. H. Stiffler 27 June 2017) that can be assessed using SCGE modeling to understand the full resilience dividend and distributional effects throughout the Cedar Rapids economy.

In turn, these findings may be compared to estimates of ROI and the NPV metrics calculated for the projects at the initial time of development and when the choice was made for which projects to take-on and further develop.

We are aware that the SCGE process is data-driven and unique to each community and its associated economy, the disturbances faced and the resilience options available (e.g., subject to budget constraints, social factors, etc.). It is clear that the SCGE resilience dividend quantification methods discussed in this paper may be better suited for the developed country context because of the extensive data requirements. Yet, once the methodology is demonstrated in a case study, it may be possible to assess the level of specificity required in the data to obtain meaningful estimates of the resilience dividend.

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